行政院國家科學委員會補助專題研究計畫成果報告

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計畫類別：☑個別型計畫　　□整合型計畫
計畫編號：NSC 89-2415-H-032-034-
執行期間：89 年 8 月 1 日至 90 年 7 月 31 日

計畫主持人：鄒 孟 文
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執行單位：淡江大學國際貿易學系

中　華　民　國　90 年 7 月 23 日

Local Learning on Computer Adoption Behavior: Evidence from Taiwan

May 2001

中 文 摘 要

本研究係利用 1992-1999 年台灣「家庭收支調查」資料來檢視網路外部性和地區性的學習效果對家用電腦擴散的影響。實證結果顯示，家庭和個人擁有或使用電腦的機率和該地區擁有或使用電腦的比例有明顯的正向關係。在控制住地區電腦擁有率或使用率的內生性質，以工具變數方法進行估計後，二者間仍有顯著的相關性。基本上，本文的的研究發現與美國的實證結果頗為一致。

Abstract

Using a relatively large sample of Taiwanese households for the period of 1992-1999, we examine network externalities or local learning in the diffusion of computer adoption. Our empirical findings suggest that the likelihood of owning (or using) a computer is strongly positively associated with the fraction of computer owners (or users) in a city. Controlling for the endogeneity of city ownership (or usage) rate, the correlation remains significant in an instrumental variables model. Our results are largely consistent with the evidence found in the United States.

Keywords: computer adoption, local learning, network externalities

1. Introduction

In spite of the substantial theoretical work on network externalities, there have been comparatively few empirical research of network effects.[1] A small literature has empirically examined technological adoption of hardware/software systems. Greenstein (1993), Gandal (1994), Saloner and Shepard (1995), and Gandal, Greenstein and Salant (1999) all provide indirect evidence that the value of the hardware depends on the variety of (compatible) complementary software. Examples include VCR technology, mainframe computers, spreadsheets market, and CD players.

Another strand of literature analyzes network externalities for the case of homegenous networks, such as automated teller machines (ATMs), automated clearing house (ACH) electronic payments systems, and fax machines (Economides and Himmelberg, 1994 Saloner and Shepard, 1995; Gowrisankaran and Starins, 2001). In such networks, the value of participating for each individual or firm increases with network size. Some recent studies of network externalities have instead utilized regional geographical cross-sectional data. Rysman (1998) considers network externalities for Yellow Pages telephone books and Goolsbee and Klenow (2000) examine network externalities in the diffusion of home computers.

Learning externalities also play an important role in technology-adoption decisions. The classic study of hybrid corn in US agriculture by Griliches (1957) provide evidence consistent with late-adoptors learning from early-adoptors. Basley and Case (1993) and Foster and Rosenzweig (1995) further use panel data and confirm the existence of learning spillovers. They find that farmers with experience of neighbors on adoption of HYV seeds are significantly more profitable than those with

[1] A survey of recent theoretical literature is provided by Economides (1996).

inexperienced neighbors.

The empirical work on neighborhood effects contains similarity to both learning and network externalities. Case and Katz (1991) find that the behaviors of neighborhood peers appear to substantially affect youth behaviors in a manner suggestive of contagion model. Similarly, Crane (1991) supports the epidemic theory of social behavior on teenage childbearing and dropping out. Evans et al. (1992) in contrast suggest that the peer group effect disappears when controlling for the endogeneity of neighbor choice. Ginther, Haveman and Wolfe (2001) report a systematic set of robustness for youth outcomes and conclude that many of the statistical correlations between neighborhood characteristics and youth outcomes in previous studies many result from the omission of reverent family background characteristics.

In the field of urban economics, externalities arguments bear considerable explanatory weight in the theoretical modeling. Lucas (1988) and Rauch (1993) both argue that the mass of human capital within cities acts to increase average productivity. Glaeser (1999) documents that faster human capital accumulation in cities is a result of learning through imitation. The probability of learning is a function of the fraction of skilled individuals in the community and the density of the community. Rauch (1993) and Glaeser and Maré (1994) conclude that the urban wage premium does not merely reflect omitted ability bias or selection effects.

In this paper, we follow the framework of Goolsbee and Klenew (2000) to examine network externalities or local learning in the diffusion of computer adoption. By using a relatively large sample of Taiwanese households for the period of 1992-1999, our empirical findings suggest that the likelihood of owning (or using) a computer is strongly positively associated with the fraction of computer owners (or users) in a city. Controlling for the endogeneity of city ownership (or usage) rate, the correlation remains significant in an instrumental variables model. Our results are largely consistent with the evidence found in the United States.

The remainder of the paper is organized as follows. In Section 2 we describe the empirical model specification. Section 3 describes the datasets. Section 4 presents computer ownership and computer use for different demographic groups. In Section 5, we analyze the empirical results. Conclusions follow in Section 6.

2. Empirical Model

To explore the influence of network externalities and local learning on computer adoption, we estimate the probability of computer adoptor following Goolsbee and Klenow (2000). The basic empirical model can be written as

$$Y_{ijt} = {}^{a}\,CITY_{jt} + \quad X^{o}_{ijt} + X^{u}_{ijt} + C^{u}_{jt} + u_{ijt} \qquad (1)$$

The dependent variable Y_{ijt} reprents the adoption decision and equals 1 if the household owns a computer and otherwise equals 0. Among the independent variables, $CITY_{jt}$ is the proportion of households in the city having a computer. If the coefficient of the $CITY_{jt}$ variable (^{a}) is positive and significant, then the network externalities or local learning exist. The people living in cities where owners are prevalent are more likely to purchase one. X^{o}_{ijt} is a vector of observed household characteristics including age, gender, marital status, education, income, the number of children between age 6 and 17 in the household, and the 9 occupation dummy variables. In practice the error term may reflect the effect of any unobservable characteristics in the X^{o}_{ijt} vector and $CITY_{jt}$ in the empirical estimation, thus we decompose the error term into three components: X^{u}_{ijt}, C^{u}_{jt}, and u_{ijt}.

The X^{u}_{ijt} represent unobserved household characteristics that are assumed to be correlated with $CITY_{jt}$ but uncorrelated with X^{o}_{ijt}. Although households may not sort themselves into cities based on their propensity to own computers, they may sort on characteristics that are correlated with the propensity. In other words, if the local spillovers arise from unobserved common traits across households, then the results will overestimate the true impacts of network externalities.

The C^u_{jt} are unobserved city-level characteristics, such as the price of computers and internet access and the density of computer stores. These variables may arise in response to city differences in computer ownership, and thus themselves represent network externalities. Finally, the u_{ijt} are unobserved household heterogeneity and unobserved household characteristics that are correlated with the observed characteristics X^o_{ijt}.

The unobservable terms in (1) clarify the potential sources of bias in estimating network externalities by directly entering $CITY_{jt}$ as explanatory variable in the model. If the measure of computer ownership rates in cities is either incomplete or endogenous, estimate of $CITY_{jt}$ could be subject to omitted variable or selection biases. The issue here is similar to that discussed in the neighborhood effects literature. The “reflection problem” proposed by Manski (1993) points out the difficulties in identifying whether the neighborhood is really influencing the individual or merely reflecting the average characteristics of the community. In our estimation model, unmeasured variables common to households are likely to upward biased estimates of network externalities (a). Similar biases could also arise from city specific unobservables (C^u_{jt}). The estimates could be either downward-biased or upward-biased.

3. Data

Two sets of data will be used in this study. The first data set is the Survey of

Family and Income Expenditure (SFIE) and the second data set is the Taiwan Social Change Survey (TSCS).

The SFIE was conducted by the Directorate-General of Budget, Accounting and Statistics (DGBAS), Taiwan. It is a large, nationally representative household survey, interviewing more than 10,000 households every year. The survey contains information on demographic characteristic, economic status, and occupation level for each member of the household. It also includes questions on the patterns of computer and other electronic goods as well as the metropolitan area of residence.[2] We restrict our sample to the heads of households between the age of 20 and 65 for the period of 1992-1997. While this survey provides us with information about the household-level computer ownership rates by city, the dataset has two limitations: (1) it does not contain a question asking people “Do you directly use a computer?”; and (2) all sample are drawn each year randomly, we cannot track household heads longitudinally and examine the timing of people who purchase their first computer.

We supplement the Taiwan Social Change Survey (TSCS) sponsored by the Taiwan National Science Council in our study.[3] The two survey years 1997 and 1999 were collected by means of face-to-face interviews, which consist of originally 2,835 and 1,948 observations respectively. For each respondent the datasets contain demographic characteristics, including gender, age, education, income, occupation, whether he/she owns a home computer, and the metropolitan area of residence. The datasets provide more information on computer use and personal attitudes towards technology. The data in 1997 contains questions on how often the respondents use their computer or the internet. The data in 1999 not only contain information on the

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[2] There are 2 municipalities (Taipei and Kaohsiung), 5 cities and 16 counties (Hsiens) in Taiwan.

[3] This research project was conducted by Dr. Hei-Yuan Chiu (1997) and Dr. Ying-Hwa Chang (1999) of the Institute of Social Sciences, Academia Sinica. The Office of Survey Research, Academia Sinica was responsible for the interviewers.

ownership of various electronic goods, questions about how often they use their computer in different life aspects, and some attitude variables such as ratings from one to five of how much they "like technology" are also included. After deleting from the two survey years those persons with missing values in terms of their age, education, or income, 2,461 and 1,774 observations were available for analysis.

4. Computer Ownership and Computer Use among Demographic Groups

Table 1 presents computer ownership for different demographic groups from SFIE data. The first three columns report the percentage of computer owners in each category, while the second three columns report the distribution of computer owners across demographic categories.

As shown from Table 1, one-fourth of households owned a computer in 1999. Computer ownership rose by 27 percentage points between 1992 and 1999. The fraction of computer ownership was highest among household heads aged 40-49. About 41.2% of male household heads and 31.1% of female household heads owned a computer in 1999. Male household heads account for almost 85 percent of computer ownership. Compared to 25.9% of household heads with only a junior high school education, 72.5% of household heads with a university (or above) education owned a computer. However, the share of computer ownership among those with university education fell about 7 percentage points during the 1990s, while the increase in the number of computer owners was observed for those with juniorlsenior high school education.

Occupational differences in computer ownership are enormous. Computer ownership in 1999 was most prevalent among professionals, managers, and technicians (at 63-79%); moderate among clerks (53%); and much lower among agricultural and laborers. The last column of Table 1 reports that technicians and managers account for 22.4% and 14.3% of computer ownership, respectively.

Table 2 shows a similar picture from TSCS data. Because the unit of analysis in this data is individual, the percentages of computer ownership among different demographic groups are much higher than those in the SFIE. The proportion of computer owners in 1999 was 60%. Computer ownership was highest among aged 20-29 and aged 40-49, more than 68% of people in these two age categories owned a computer. There is an increasing relationship between education and computer ownership. Compared to 41.3% of people with junior high school education, 89.9% of people with university (or above) education owned a computer. While professionals and managers have highest rates of computer ownership (88.4% and 81.6%), students account for 23.4% of computer ownership.

With respect to computer adoption, one-third of respondents in 1997 used a computer. As cloumn 2 shows, young people used computers more than older people. Computer use peaked at 66.5% among 20-29 years old and dropped to 10.2% among 50-65 years old. The link between computer use and education is also strong. Computer use among university (or above) graduates was 82.3%, which is far higher than that among junior high school graduates (13.1%). Men use computers more than women do – 36.4% of men and 30.7% of women used computers. Similar to the pattern of computer ownership, computer use was most prevalent among professionals, technicians, and clerks (at 68-73%), which accounts for about one-half of computer usage.

5. Empirical Results

In this section we use two empirical models to explore the impact of network externalities or local learning on computer ownership. Our approach in this study is first to estimate the computer ownership (or adoption) regressions by probit and then to estimate the instrumental variable model, controlling for the endogeneity of the city ownership rate.

5.1. Pooled Cross-Sectional Time-Series Data on Computer Ownership (SFIE)

We begin our analysis by presenting the pooled cross-sectional time-series regressions of computer ownership. Using the SFIE data, the regressions are estimated with year controls. The year effects capture the computer's price and other factors that might evolve with time, such as technology awareness. Table 3 presents the results of probit regressions with and without instrumenting for $CITY_{jt}$. In each of the equations, the fraction of households in the city who own computers, which can be proxied as local learning or network externalities is included as an independent variable, along with the household characteristics. The point estimate of 1.85 in column 1 implies that, controlling for household-specific characteristics, a non-owner in a city with 10 percentage points higher computer ownership has a 5 percentage points higher probability of owning a computer.

With respect to the household variables, the coefficients generally have predictable signs. Households with more income and education are more likely to own computers. Computer ownership is 25 percentage points higher for 40-49 years old relative to 20-29 years old. Working in a public sector, professionals, and having more children between 6 and 17 years old in the household are also associated with a higher probability of computer ownership. Furthermore, the rate of computer ownership rises rapidly during the 1990s.

While the results in column 1 suggest the existence of strong network externalities and local learning, there are several potential sources of bias in estimating network externalities. If the local spillover comes from unobservable common traits across households in a city, the estimates of $CITY_{jt}$ are likely to be biased upward. For this reason, in column 2 we include 3 dummies for ownership of other consumer electronics (stereo, VCR, LD player) as proxies for unobservable technological sophistication among households. The three dummies have the expected signs and are statistically significant. The inclusion of proxies for household unobservables leads the coefficient on $CITY_{jt}$ to fall from 1.85 to 1.69, but remains statistically significance at 1% level. Since these additional controls tend to be associated with a household's unobserved technology sophistication, our results suggest that the strong local learning and network externalities does not merely reflect the correlation between $CITY_{jt}$ and X^{u}_{ijt}.[4]

We further model the potential endogeneity of network externalities by using instrumental variable (IV) method. Instruments are constructed for $CITY_{jt}$ which are correlated with $CITY_{jt}$ but not correlated with household unobservables (X^{u}_{ijt}). We use 8 metropolitan area characteristics as instruments, which include gender ratio, average household income, the proportion of college (or above) graduates, the employment share of industrial sector, the number of students, the fraction of stereo ownership, the fraction of VCR ownership, and the fraction of LD player ownership.

One might question that if the average characteristics of the city (X^{o}_{jt}) are valid instruments, i.e., uncorrelated with unobserved household characteristics (X^{u}_{ijt}). Since we specify X^{u}_{ijt} is orthogonal to X^{o}_{ijt}, X^{u}_{ijt} is defined as a component of household unobservables that is correlated with $CITY_{jt}$ conditional on the observed household characteristics (X^{o}_{ijt}). We further clarify u_{ijt} term as the household unobservables that is correlated with household observables (X^{o}_{ijt}). Under this specification, correlation between household observables and unobservables may biases the coefficients on X^{o}_{ijt}, but not the a coefficient on $CITY_{jt}$.

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[4] Due to lack of household panel data, we cannot control for unobserved household heterogeneity. This may introduce further omitted variable bias if the unobserved heterogeneity is correlated with the

Column 3 and column 4 report instrumental variable estimates, which are intended to control for the endogeneity of $CITY_{jt}$.[5] We calculate the correct asymptotic covariance matrix using LIMDEP econometric software (Greene, 1995). Comparing these results with computer ownership regressions that treat $CITY_{jt}$ as exogenous suggests that the estimated positive effect of network externalities is upward-biased. Column 4 shows the estimates when one controls for household unobservables and instruments for the $CITY_{jt}$ term. The coefficient on $CITY_{jt}$ further fall from 1.69 (column 2) to 1.54 (column 4), but again, we find strong evidence of network externalities. The other regressors generally do not vary greatly across the two specifications. The Hausman tests show that the differences between the estimates of these two specifications are statistically significant. Thus, we reject the hypothesis that network externalities are exogenous.

To summarize, after controlling for the endogeneity of computer ownership rate in the city, our results support the existence of network externalities and local learning. The local spillovers cannot be explained by common unobserved traits among households. These findings are largely consistent with the evidence reported by Goolsbee and Klenow (2000) for a U.S. household sample.

5.2. Cross-sectional Data on Computer Ownership and Computer Use (TSCS)

The TSCS data complements the information on computer adoption and Internet use, and also include questions on asking people how frequently they use a computer or the internet. Unlike the SFIE data, the unit of analysis for this dadaset is individual.

Table 4 presents the probit regressions for computer ownership, computer adoption and internet use. The first three columns of estimation are taken from 1997

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explanatory variables.

[5] We use 8 metropolitan area characteristics as instruments for computer ownership rate, and include 3 dummies for ownership of other consumer electronics as direct control variables. Goolsbee and Klenow (2000) do not present IV models that control for households' technological sophistication.

survey, while the last three columns are drawn from 1999 survey. Column 1 and column 4 show that a higher rate of computer ownership in a city is associated with a higher probability of computer ownership. Computer ownership is significantly higher for educated people, and positively correlated with personal income level. The age profiles of computer ownership in 1999 are similar to those in SFIE data. Compared with people aged between 20 and 29, computer ownership is 44.4 percentage points higher for people aged between 40 and 49, but 24.5 percentage points lower for people aged between 33 and 39.

The evaluation of "attitude towards technology" in 1999 survey was measured with two questions, which include "Do you agree with the below statements on computers?" (Attitude 1): (1) the computer is a necessary instrument at work; (2) computers have much influence in our life; (3) one will be behind the times if he/she does not know how to use a computer; and (4) it would be a heavy loading if one has to learn more computer knowledge, and "How well the below statements can describe your personality?" (Attitude 2): (1) I will make great efforts on obtaining more revelvent computer knowledge; (2) I will use a computer to handle more practical issues; and (3) I will try to use a computer for entertainment purpose. The answer of each item was coded as five scale points (1 to 5) ('strongly disagree'(1), 'disagree'(2), 'O.K.'(3), 'agree'(4), and 'strongly agree'(5)). We use the average scores of the two questions as our proxies for personal attitude towards technology.

As shown from column 4, the two attitude variables and the three dummies for other consumer electronics (stereo, pickup camera, and LD player) all have significant and positive impacts on computer ownership. The inclusion of the attitude variables causes the coefficient on $CITY_{jt}$ to drop to 1.67, but the strong local learning effect is reaffirmed.

Turning to the regressions of computer adoption and internet use. Column 2 and column 3 show that computer users and internet uses are prevalent among young and educated people. Men use computers more than women. As expected, people who living in a city with higher fraction of computer usage are more likely to use computers. The likelihood of using the internet is also positively associated with the fraction of internet users in a city, which suggests that computers are components of local communications networks. The local spillovers also appear to come from users for work (column 5) and those who use computers for dealing with personal and home affairs (column 6).

Table 5 reports the instrumental-variables estimates of network externalities by using 8 metropolitan area characteristics as instruments for $CITY_{jt}$. Compared to the simple probit estimates in Table 4, the instrumental-variables estimators of $CITY_{jt}$ tend to fall in value but remain statistically significance after controlling for the endogeneity of network externalities.

The network and learning spillovers theory predict that experienced, heavy users should have more influences on adoptors. Since the 1997 Survey from TSCS data provides more detailed information on the frequency of people using computers and the internet, the six response categories can be coded as 0, 1,…, 5 respectively ('never use'(0), 'use it once in several months'(1), 'use it every month'(2), 'use it every week'(3), 'use it every 2 or 3 days'(4), and 'use it almost everyday'(5)). We identify two computer (or internet) usage groups: people who use a computer (or the internet) almost everyday as "heavy users" and those who use it once in several months as "light users". Using this classification of computer (or internet) usage, we can construct two city share variables: the proportion of heavy users in a city and the proportion of light users in a city. The regressions of computers adoption and internet use can be estimated by using an ordered probit model. The results are presented in Table 6.

Construction of an estimate of the marginal effects of $CITY_{jt}$ on the frequency of computer (or internet) usage within an ordered probit model is not straightforward. To gauge the approximate net effect, we estimate the marginal effect of $CITY_{jt}$ on the frequency of computer (or internet) usage for different subsets of our sample. To measure the marginal effect of $CITY_{jt}$ on the Prob(C=1), we consider only those reporting C=1, and likewise for C=2 through C=5. With each subsample, we construct the average of the constructed marginal values. For any single respondent, these marginal effects would sum to zero because the probabilities add to one. However, our subsampling allows one simple way to gauge what might be treated as the "net" effect our sample implies, given the estimated parameters and distribution of people across respondents. Column 1 and column 3 show that the net effects are positive for both computer adoption and internet usage models. Higher values of computer adoption share (or internet usage share) in the city are more likely associated with increases in the frequency of computer adoption (or internet usage).

Column 2 and Column 4 indicate that spillovers appear to be larger from those who use computers or the internet more frequently. The coefficient on the share of heavy computer adoptors is 1.17 compared to 0.62 on the share of light computer adoptors. Similarly, the coefficient on the share of heavy internet users is 6.58 compared to 0.38 on the share of light internet users.

We further try to investigate whether local schools or the local computer stores play important roles in arising the spillovers. One potential explanation for the strong local learning effect can be driven by the high propensity of computer use in local schools. To evaluate this possibility, we estimate the standard IV regressions restrict to only households without school-age children in the SIFE data. In Table 7, column 1 reports the coefficient of city ownership is again significant and has a slightly higher magnitude (1.64) as the corresponding IV estimate for the total sample in column 4 of

Table 3 (1.54).

Another explanation of local spillover effect is that households in a city with higher computer ownership rate are surrounded by a dense network of computer stores, which increases the probability of computer purchase behavior. In other words, cities with lots of households own a computer may endogenously have a large number of computer stores or a dense network of computer retailers. As column 2 shows, the local learning effect still exists even including the number of computer stores in a city as an instrument. Therefore, the school system or the local computer stores cannot directly explain the local spillovers for the households.

We also examine the local learning effect by using a more detailed local data. In the SFIE data, each city/county are classified into three strata of city, town and village according to the employment structure in industry (based on the household registration data).[6] There are 44 city strata, 21 town strata, and 21 village strata in Taiwan. Column 3 shows that the IV estimate of ownership share at a more detailed metropolitan level (1.40) is somewhat lower than the comparable estimate in column 4 of Table 3 (1.54) but remains statistically significant. Thus, we suggest the presence of local learning effects in a more detailed stratification data.

6. Conclusions

This paper analyzes the extent of network externalities or local learning on computer adoption in Taiwan. Using a nationally representative sample of Taiwanese households for the period of 1992-1999, we find strong evidence of local learning effects. People who living in a city with higher fraction of computer ownership (or usage) are more likely to own (or use) computers. The local spillovers from interest usage are also confirmed in our study.

[6] Taipei Municipality has 12 Ch'us and Kaohsiung Municipality has 11 Ch'us.

Performing several tests, we find that the local effects are not merely driven by common unobservables or by alternative network explanations such as local schools or local computer stores. Both the simple probit and instrumental variables models suggest the robustness of our basic findings. These results are consistent with the evidence for the United States.

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Table 1 Computer Ownership among Demographic Groups (SFIE)

	% who own computers			% of computer owners who are		
	1992	1995	1999	1992	1995	1999
All households	12.2	20.4	39.3			
Age						
20-29	8.4	15.7	37.9	8.1	8.2	8.3
30-39	9.4	17.4	40.1	28.9	29.7	27.9
40-49	16.8	26.5	53.0	38.3	40.9	42.2
50-65	13.1	18.8	38.1	24.7	21.1	21.5
Education						
< Junior High	5.6	11.2	19.7	15.4	16.6	14.3
Junior High	5.4	9.5	25.9	8.1	8.5	10.8
Senior High	12.0	19.3	42.4	26.5	26.9	31.1
Junior College	20.8	36.9	60.0	18.5	22.0	19.8
University +	36.7	49.2	72.5	31.5	25.9	24.0
Gender						
Male	12.4	20.8	41.2	89.6	88.2	84.9
Female	10.7	21.8	31.3	10.4	11.8	15.1
Occupation						
Managers	30.6	44.6	71.5	20.7	16.7	14.3
Professionals	35.5	51.0	78.7	18.5	15.5	11.4
Technicians	20.5	32.5	62.9	17.8	20.9	22.4
Clerks	16.3	25.8	52.9	7.4	6.9	7.5
Service	9.5	15.7	38.8	12.7	11.4	13.9
Agricultural	1.8	4.8	12.7	1.3	1.8	2.3
Craftsmen	5.5	11.4	33.1	10.2	11.1	11.5
Operators	6.0	12.7	31.5	6.0	9.6	11.4
Laborers	3.8	9.3	20.7	1.6	2.5	2.5
Others	11.6	17.0	11.6	3.9	3.5	2.9

Table 2 Computer Ownership and Computer Adoption among Demographic Groups (TSCS)

	% who			% of		
	Own Computers	Use Computers	Own Computers	Computer Owners who are	Computer Users who are	Computer Owners who are
	1997 Survey		1999 Survey	1997 Survey		1999 Survey
All households	39.9	33.6	60.0			
Age						
20-29	54.0	66.5	68.1	27.5	38.6	27.2
30-39	35.9	44.2	53.7	25.1	35.0	24.7
40-49	43.4	27.9	68.8	27.8	20.1	32.1
50-65	35.7	10.2	48.6	19.5	6.3	16.1
Education						
< Junior High	22.5	1.7	38.0	17.0	1.7	16.5
Junior High	29.4	13.1	41.3	10.3	5.9	10.2
Senior High	42.2	42.6	60.9	30.6	36.0	28.7
Junior College	62.7	76.0	78.9	21.7	30.2	19.4
University +	73.4	82.3	89.9	20.3	26.2	25.2
Gender						
Male	39.5	36.4	59.5	49.8	45.3	51.8
Female	40.4	30.7	59.8	50.2	54.7	48.2
Occupation						
Managers	56.8	62.3	81.6	7.2	9.4	10.5
Professionals	66.7	73.2	88.4	8.5	10.6	11.6
Technicians	57.7	70.1	68.1	15.7	21.7	12.5
Clerks	52.1	67.7	77.1	10.2	15.5	11.4
Service	37.8	22.2	58.7	10.0	6.7	11.0
Agricultural	16.3	0.9	27.8	2.4	0.2	2.2
Craftsmen	29.6	20.2	41.3	8.6	7.0	7.9
Operators	27.5	15.8	49.3	6.0	4.1	6.4
Laborers	23.0	13.2	34.3	3.6	2.4	3.1
Students	41.4	26.9	58.4	27.9	22.5	23.4

Table 3 Household Ownership of Computers (SFIE)[a]

Variable	Ownership Share as Exogenous		Ownership Share as Endogenous[b]	
	(1)	(2)	(3)	(4)
Constant	-2.6471 (-75.03)***	-2.8005 (-77.18)***	-2.5992 (-221.20)***	-2.7577 (-236.73)***
Age 30-39	-0.1588 (-8.37)***	-0.1490 (-7.73)***	-0.1567 (-21.31)***	-0.1470 (-20.27)***
Age 40-49	0.2535 (12.50)***	0.2750 (13.35)***	0.2552 (30.84)***	0.2768 (33.92)***
Age 50-65	0.1979 (8.98)***	0.2406 (10.75)***	0.1999 (22.48)***	0.2428 (27.67)***
Junior High	0.0425 (2.54)***	0.0203 (1.20)	0.0431 (7.16)***	0.0209 (3.51)***
Senior High	0.2652 (17.27)***	0.2161 (13.86)***	0.2672 (42.55)***	0.2179 (35.04)***
Junior College	0.5571 (28.74)***	0.4953 (25.18)***	0.5601 (61.05)***	0.4979 (54.75)***
University	0.7143 (33.57)***	0.6435 (29.82)***	0.7186 (67.73)***	0.6477 (61.51)***
Male	0.0523 (3.54)***	0.0251 (1.67)*	0.0486 (8.06)***	0.0213 (3.58)***
Married	0.2477 (13.60)***	0.1795 (9.66)***	0.2445 (36.60)***	0.1761 (26.68)***
Kids Age 6-17	0.0330 (6.43)***	0.0423 (8.13)***	0.0328 (15.44)***	0.0421 (20.05)***
Income	0.0004 (29.85)***	0.0003 (21.48)***	0.0004 (65.32)***	0.0003 (47.53)***
Public Sector	0.0808 (5.89)***	0.0776 (5.59)***	0.0786 (11.50)***	0.0750 (11.07)***
Stereo		0.3019 (29.59)***		0.2999 (67.06)***
VCR		0.2831 (24.70)***		0.2889 (66.55)***
LD		0.3489 (17.68)***		0.3497 (32.75)***
Ownership Share	1.8461 (41.10)***	1.6921 (37.03)***	1.6907 (78.92)***	1.5384 (72.41)***
Year 93	0.0287 (1.42)	0.0354 (1.73)*	0.0040 (0.61)	0.0130 (2.00)**
Year 94	0.0569 (2.84)***	0.0719 (3.55)***	0.0051 (0.75)	0.0256 (3.79)***
Year 95	0.1538 (7.40)***	0.1808 (8.58)***	0.1218 (15.81)***	0.1533 (20.05)***
Year 96	0.2181 (10.55)***	0.2490 (11.84)***	0.1789 (21.58)***	0.2159 (26.17)***
Year 97	0.2862 (13.49)***	0.3330 (15.40)***	0.2957 (33.41)***	0.3449 (39.12)***
Year 98	0.3495 (15.96)***	0.4052 (18.11)***	0.4021 (43.63)***	0.4571 (49.77)***
Year 99	0.5787 (25.53)***	0.6632 (28.48)***	0.6328 (64.13)***	0.7172 (72.80)***
Log-likelihood	-45486.68	-44263.93	-45599.74	-44363.45

a. The number of observations is 106,339. All regressions include dummy variables for 9 occupations. Figures in parentheses are t-statistics. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels respectively.

b. Ownership share is instrumented using 8 metropolitan area characteristics.

Table 4 Computer Ownership, Computer Adoption and Internet Use Probit Model (TSCS)[a]

Variables	1997 Survey	1997 Survey	1997 Survey	1999 Survey	1999 Survey	1999 Survey
	Computer Ownership (1)	Computer Adoption (2)	Internet Use (3)	Computer Ownership (4)	Work Aspect (5)	Home Aspect (6)
Constant	-1.6784 (-9.78)***	-1.8247 (-8.03)***	-3.3323 (-6.21)***	-3.1382 (-11.04)***	-4.0900 (-11.40)***	-4.3691 (12.38)***
Age 30-39	-0.3103 (-3.46)***	-0.3517 (-3.61)***	-0.1336 (-1.04)	-0.2452 (-2.22)**	-0.3369 (-2.71)***	-0.3032 (-2.62)***
Age 40-49	0.1213 (1.20)	-0.5576 (-4.93)***	-0.4253 (-2.57)***	0.4442 (3.60)***	-0.2640 (-1.92)*	-0.2321 (-1.82)*
Age 50-65	0.2293 (1.97)**	-0.9522 (-6.67)***	-0.8500 (-3.49)***	0.2889 (2.09)**	-0.6245 (-3.86)***	-0.5822 (-3.82)***
Junior High	0.2583 (2.63)***	0.6737 (4.39)***		-0.0732 (-0.62)	0.3701 (2.29)**	0.1809 (1.20)
Senior High	0.5960 (6.54)***	1.2963 (9.24)***	1.0749 (3.36)***	0.1636 (1.41)	0.8407 (5.68)***	0.5445 (3.97)***
Junior College	0.9699 (8.55)***	1.9720 (12.55)***	1.7271 (5.35)***	0.5209 (3.43)***	1.4914 (8.24)***	1.0075 (6.14)***
University	1.1691 (9.31)***	2.2308 (13.18)***	2.3309 (7.18)***	0.8285 (4.94)***	1.7153 (8.54)***	1.3864 (7.82)***
Male	-0.0544 (-0.85)	0.1795 (2.27)***	0.1103 (1.11)	-0.0224 (-0.27)	0.1121 (1.11)	0.2965 (3.25)***
Married	-0.0681 (-0.81)	-0.1476 (-1.57)	-0.3994 (-3.28)***	0.1503 (1.66)*	-0.2609 (-2.42)**	-0.0472 (-0.47)
Income	0.0016 (1.71)*	0.0017 (1.55)	0.0010 (0.84)	0.0001 (0.07)	0.0031 (1.58)	0.0002 (0.10)
Attitude 1				0.0239 (1.69)*	0.0880 (5.17)***	0.0795 (5.12)***
Attitude 2				0.0690 (5.03)***	0.1076 (6.38)***	0.1240 (7.81)***
Stereo				0.3986 (4.66)***	0.1461 (1.32)	0.2023 (1.95)**
Camera				0.4433 (4.87)***	0.2874 (2.84)***	0.2283 (2.51)***
LD				0.4925 (5.95)***	0.1586 (1.49)	0.1592 (1.62)
Ownership Share	1.9121 (8.05)***			1.6717 (6.97)***		
Adoption Share		1.2915 (4.20)***				
Internet Share			3.3657 (3.21)***			
Work Share					1.5530 (5.18)***	
Home Share						1.3778 (4.62)***
Log-likelihood	-1434.55	-1628.17	-491.21	-876.14	-585.46	-711.76
N	2461	2437	917	1774	1774	1774

a. N is the number of observations. All regressions include dummy variables for 9 occupations. Figures in parentheses are t-statistics. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels respectively.

Table 5 Computer Ownership, Computer Adoption and Internet Usage
Instrumental Variable Method (TSCS)[a]

Variables	1997 Survey	1997 Survey	1997 Survey	1999 Survey	1999 Survey	1999 Survey
	Computer Ownership (1)	Computer Adoption (2)	Internet Use (3)	Computer Ownership (4)	Work Aspect (5)	Home Aspect (6)
Constant	-1.5990 (-17.24)***	-1.7808 (-24.17)***	-3.2933 (-81.07)***	-3.0539 (-23.51)***	-4.0641 (-40.09)***	-4.2607 (-40.20)***
Age 30-39	-0.2924 (-5.65)***	-0.3445 (-7.21)***	-0.1292 (-3.55)***	-0.2267 (-4.14)***	-0.3277 (-6.74)***	-0.2899 (-5.52)***
Age 40-49	0.1476 (2.50)***	-0.5473 (-10.22)***	-0.4161 (-11.33)***	0.4594 (7.80)***	-0.2483 (-4.70)***	-0.2155 (-3.79)***
Age 50-65	0.2594 (3.95)***	-0.9378 (-16.53)***	-0.8371 (-23.20)***	0.2962 (4.36)***	-0.6134 (-10.48)***	-0.5676 (-9.07)***
Junior High	0.2891 (5.52)***	0.6742 (17.54)***		-0.0621 (-0.97)	0.3743 (7.67)***	0.1752 (3.42)***
Senior High	0.6228 (12.46)***	1.3064 (32.06)***	1.0853 (57.70)***	0.1780 (2.94)***	0.8496 (16.57)***	0.5500 (10.27)***
Junior College	1.0057 (15.68)***	1.9867 (36.08)***	1.7413 (43.95)***	0.5449 (7.30)***	1.5098 (23.11)***	1.0199 (14.32)***
University	1.2082 (17.50)***	2.2530 (38.38)***	2.3496 (45.55)***	0.8470 (11.30)***	1.7359 (27.03)***	1.4048 (19.68)***
Male	-0.0713 (-2.01)**	0.1737 (6.03)***	0.1056 (4.64)***	-0.0302 (-0.80)	0.1083 (3.51)***	0.2892 (8.39)***
Married	-0.0681 (-1.40)	-0.1438 (-3.29)***	-0.3981 (-11.71)***	0.1479 (3.32)	-0.2599 (-6.95)***	-0.0564 (-1.41)
Income	0.0018 (3.49)***	0.0018 (4.12)***	0.0011 (2.73)***	0.0002 (0.31)	0.0030 (4.87)***	0.0003 (0.40)
Attitude 1				0.0263 (3.89)***	0.0892 (15.86)***	0.0798 (12.96)***
Attitude 2				0.0676 (9.73)***	0.1062 (18.51)***	0.1227 (20.03)***
Stereo				0.4000 (8.76)***	0.1506 (4.31)***	0.2079 (5.53)***
Camera				0.4427 (11.27)***	0.2866 (8.23)***	0.2293 (5.90)***
LD				0.5018 (11.48)***	0.1745 (5.16)***	0.1723 (4.70)***
Ownership Share	1.6470 (11.43)***			1.4694 (12.34)***		
Adoption Share		1.1512 (8.28)***				
Internet Share			2.8947 (11.17)***			
Work Share					1.4645 (14.89)***	
Home Share						1.1223 (9.19)***
Log-likelihood	-1446.62	-942.89	-492.45	-883.20	-587.92	-716.35
N	2461	2437	917	1774	1774	1774

a. N is the number of observations. All regressions include dummy variables for 9 occupations. Eight metropolitan area characteristics are used as instruments. Figures in parentheses are t-statistics. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels respectively.

Table 6 Computer Adoption and Internet Usage Ordered Probit Model (TSCS)[a]

Variables	1997 Survey	1997 Survey	1997 Survey	1997 Survey
	Computer Adoption (1)	Computer Adoption (2)	Internet Use (3)	Internet Use (4)
Adoption Share	0.9587 (3.56)***			
Adoption Share – Heavy Users		1.1653 (2.49)***		
Adoption Share – Light Users		0.6234 (0.94)		
Internet Share			3.2052 (2.92)***	
Internet Share – Heavy Users				6.5846 (2.04)**
Internet Share – Light Users				0.3835 (0.15)
MU(1)	0.3149 (13.47)***	0.3148 (13.46)***	0.2535 (7.85)***	0.2537 (7.83)***
MU(2)	0.4880 (17.27)***	0.4880 (17.28)***	0.4265 (10.11)***	0.4274 (10.04)***
MU(3)	0.7297 (21.60)***	0.7298 (21.60)***	0.7037 (12.96)***	0.7062 (12.79)***
MU(4)	1.0449 (26.95)***	1.0453 (26.97)***	1.1623 (14.61)***	1.1672 (14.51)***
Marginal Effects of Adoption Share[b]				
P(C=0)	-0.316(1514)			
P(C=1)	0.069(165)			
P(C=2)	0.040(89)			
P(C=3)	0.053(119)			
P(C=4)	0.058(143)			
P(C=5)	0.096(407)			
Marginal Effects of Internet Share[c]				
P(I=0)			-0.915(683)	
P(I=1)			0.195(57)	
P(I=2)			0.131(34)	
P(I=3)			0.188(46)	
P(I=4)			0.222(52)	
P(I=5)			0.180(45)	
Log-likelihood	-2226.59	-2226.45	-800.67	-799.93
N	2437	2437	917	917

a. N is the number of observations. All regressions include 3 age dummies, 4 education dummies, gender dummy, dummy variable for marital status, and 9 occupation dummies. Figures in parentheses are t-statistics. *** and ** represent statistical significance at 1% and 5% levels respectively.

b.c. These marginal effects are calculated for each individual and averaged across the different subsamples corresponding to each group. The numbers in parentheses alongside each estimate correspond to the number of observations in each group.

Table 7 Sources of Network (SFIE)[a]

Variables	Households without School-age Children	Computer Stores as an instrument	Three Strata of City, Town and Village
	(1)	(2)	(3)
Ownership Share	1.6439 (57.23)***	1.7394 (38.72)***	1.4020 (71.36)***
Log-likelihood	-17870.97	-10147.37	-44396.98
N	51530	27591	106339

a. N is the number of observations. All regressions include independent variables as listed in Table 3. Ownership share is instrumented using 8 metropolitan area characteristics. Figures in parentheses are t-statistics. *** represents statistical significance at 1% level.

b. Column 2 only contains 1992 and 1996 surveys. The number of computer stores in a city is also included as an instrument.